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PRELIMINARY NEURAL NETWORK DETECTION OF A GULF STREAM IN IMAGES OF SEA SURFACE TEMPERATURE GRADIENTS

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A concept is tested for automatically identifying Gulf Stream surface temperature gradients among the myriad fronts discernable as edges in satellite infrared imagery. The concept is to utilize the techniques of neural networks in concert with a principal component climatology of Gulf Stream axes. Sample neural networks were constructed that successfully produced mode coefficients for the first three components for a large set of well defined Gulf Streams. One network, operating on a jumble of edges from a real composite sea surface temperature image, produced a 3-mode Gulf Stream sufficiently close to the actual Gulf Stream edges as to hold promise for identifying the Gulf Stream's gradients automatically.

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SUMMARY

As a Phase I effort of the Small Business Innovative Research (SBIR) Program, this work tests the feasibility of an approach to solve a problem announced in the SBIR solicitation of October 1987. This final report for Phase I shows that a concept proposed by Planning Systems, Incorporated (PSI) to address topic N88-6, the identification of tactically significant acoustic environments, has demonstrated feasibility and warrants follow-on funding in Phase II. PSI's approach is to use neural network technology in concert with complex empirical orthogonal function (CEOF) decomposition of the Gulf Stream and a Naval Ocean Research and Development Activity (NORDA) edge detection procedure, to identify the Gulf Stream in infrared (IR) imagery of the western North Atlantic Ocean.

Acknowledgments

The work was performed under contract with the Office of Naval Research. The support of Ron Holyer, Sarah Peckinpaugh and Matt Lybanon of NORDA in both technical interactions and in providing access to their facilities was crucial to our progress. The effort was substantially aided by the performance of other PSI employees -- Helen Beresford, Sam Oriol and Dick Crout who identified, selected, and provided edge and IR imagery using NORDA computer facilities, and Kathryn Bush who worked through the CEOFs and displayed the ten dominant modes.

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PRELIMINARY NEURAL NETWORK DETECTION OF A GULF STREAM IN IMAGES OF SEA SURFACE TEMPERATURE GRADIENTS

1.0 INTRODUCTION AND BACKGROUND

1.1 Introduction

The sea surface is teeming with thermal structure detectable by satellite infrared sensors. Present sensors are capable of 1 km horizontal resolution with 0.5°C accuracy under cloud-free conditions (Figure 1). Such sensors can detect ocean fronts, shingles, rings, and eddies -- structures caused by a variety of atmospheric, oceanographic, and coastal processes. For Naval applications, however, only those with deep reaching (on the order of 100 m) variation in sound speed are of tactical significance.

The opportunity exists to select from the wide variety of surface thermal structures those associated with deep reaching sound speed variations. We know that in the Western Atlantic the Gulf Stream is important tactically as are the rings (cold and warm core) that it spawns[1]. The Gulf Stream and its rings contribute to the surface thermal expressions observed by satellite. Specifically the Gulf Stream is a continuous feature consisting of sea surface temperature gradients between the longitudes 75°W and 40°W. Images can be produced in which pixels have been identified that are associated with high horizontal gradients and thus are candidates for the Gulf Stream edge (Figure 2). The problem becomes to discard some of these high gradient edges and connect the rest into a continuous Gulf Stream. A mathematical description of a continuous Gulf Stream with realistic meanders has been defined using complex empirical orthogonal functions (CEOFs)[2]. Ten complex modes give a good description (Figures 3) and serve as a compact description of the tactically significant features.

The innovative opportunity is to use the new technology of neural networks to connect the gradients of infrared imagery to the complex modes of a continuous, tactically significant Gulf Stream. If applied successfully, then the great speed and quantitative effectiveness of artificial intelligence technology can be brought to bear on the identification of tactically significant environments from remotely sensed imagery, making more effective the U.S. Navy staff assigned to the task in the Fleet.

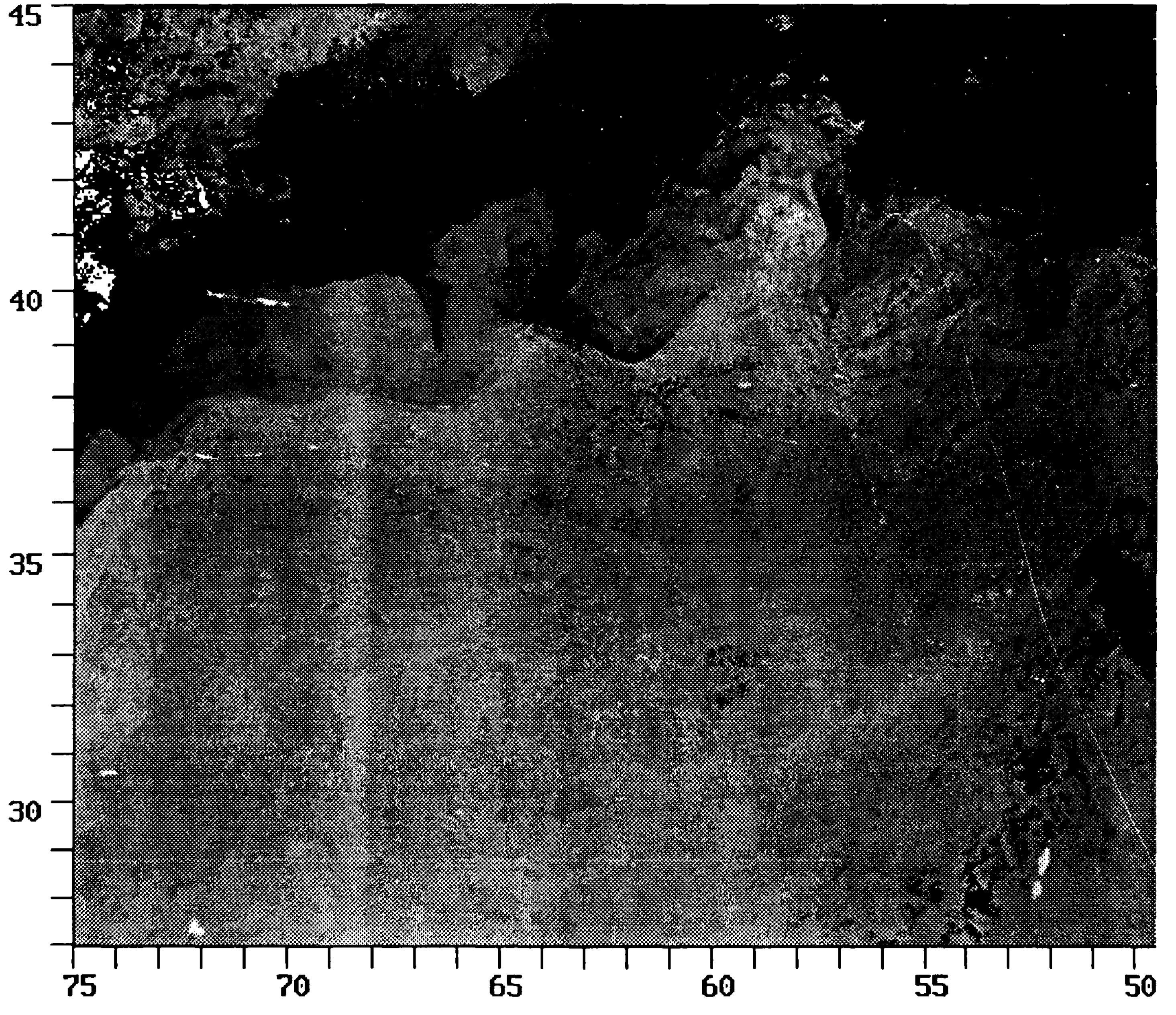


Figure 1. Sea Surface Temperature image derived from infrared (IR) satellite imagery.

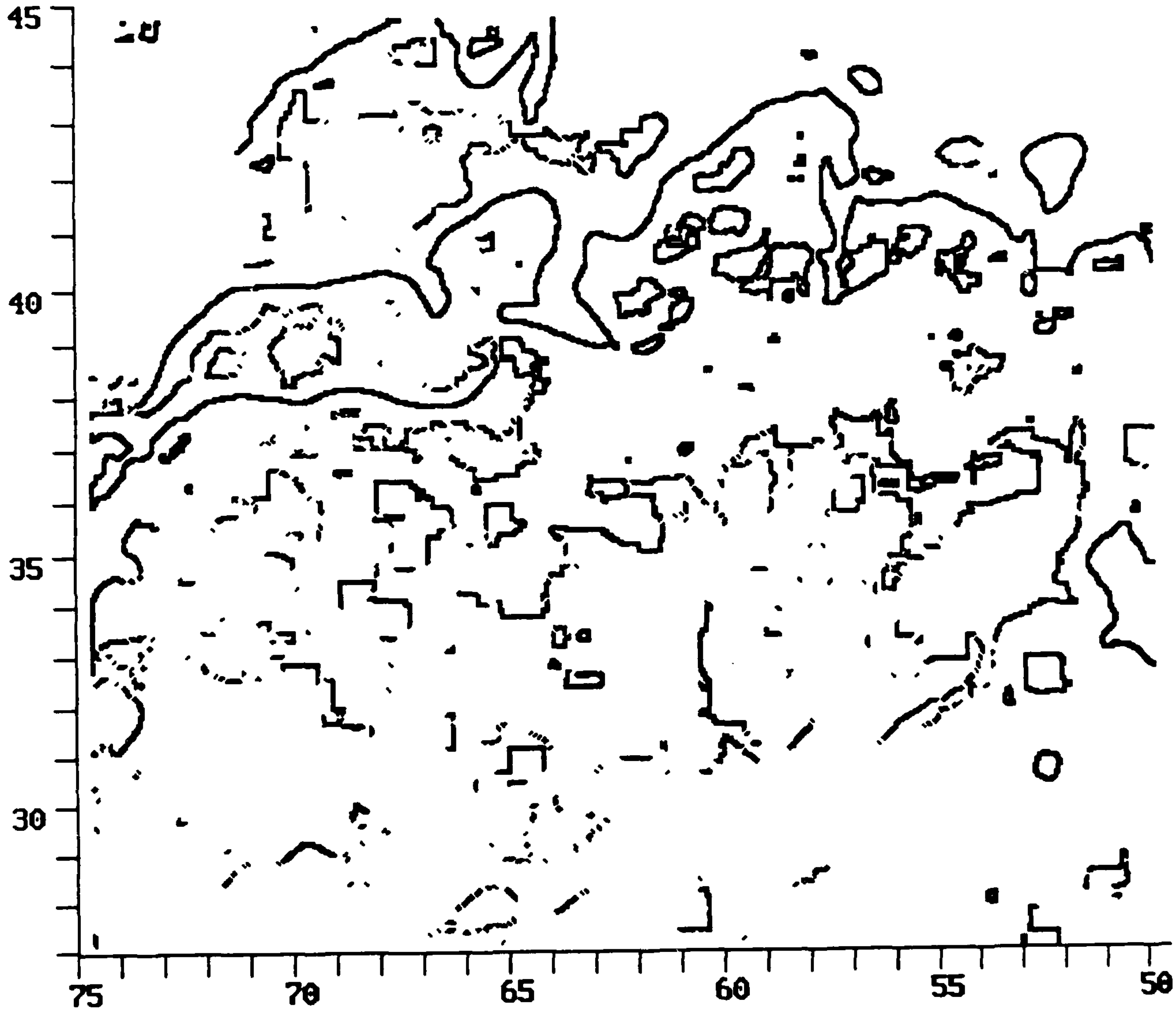


Figure 2. Edge image derived from Figure 1 using the Naval Ocean Research and Development Activity (NORDA) edge detection procedures.

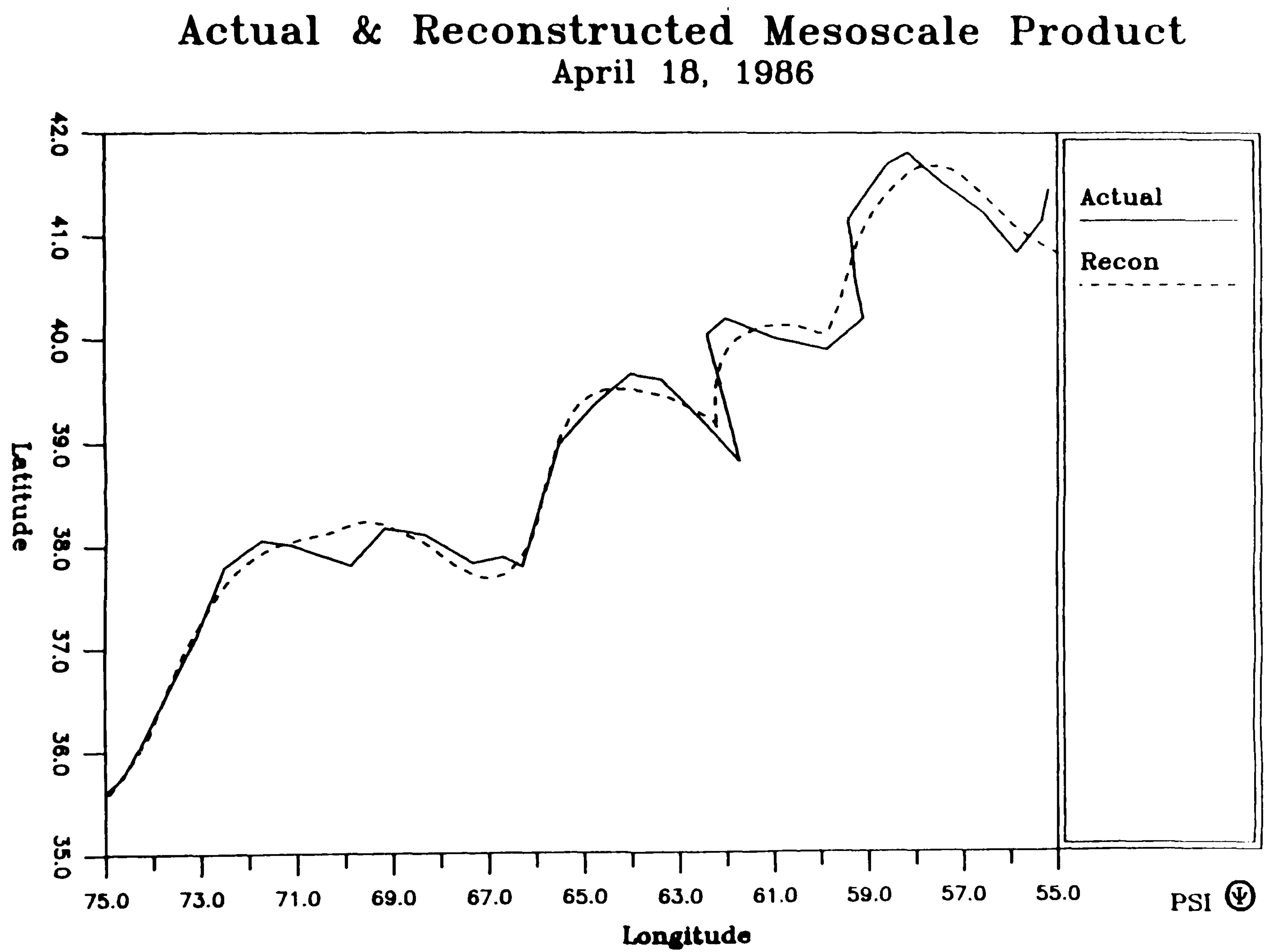


Figure 3. Capacity of 10 Complex Empirical Orthogonal Functions) (CEOFs) to reconstruct (dashed line) even a convoluted Gulf Stream produced by an analyst (solid line).

The emerging capabilities of neural networks to reduce noisy imagery to meaningful information in a fast, highly parallel fashion presents an opportunity to solve longstanding problems in satellite data analysis. A neural network implemented in either software or hardware greatly decreases the need for a human operator to visually examine the infrared imagery since the network operates directly on the data to produce probable Gulf Stream points. This computer implementation yields another immediate benefit -- the processing begins as soon as the satellite data are acquired instead of waiting for a human expert to analyze the data. The necessity for specialized shore based display equipment and interactive software are also diminished because the network operates on the digital data directly as it is received from the satellite or automatically processed by existing edge detection algorithms.

In addition to countering the deficiencies in the present system, a neural network capable of analyzing infrared imagery opens up new possibilities in tactical use of satellite data. The capability to analyze satellite imagery without the use of an expert and extensive workstation introduces the possibility of on-board analysis of data. This enables properly equipped vessels to make critical decisions based on the latest information in near real-time without the delays introduced by the present system and its dependence on shore-based facilities.

1.2 Background

Planning Systems Incorporated (PSI) developed a numerical description of the Gulf Stream based on complex empirical orthogonal functions (CEOFs) -- the eigenvectors of an "expectation matrix." The expectation matrix is obtained by averaging a set of matrices each representing the correlation properties of an individual vector -- in our case a vector that describes the instantaneous position of the Gulf Stream. This formulation and its advantages for describing the Gulf Stream are described in detail by Carter[3]. To summarize that reference, a looping, contorted, but continuous Gulf Stream can be described by a vector of complex elements consisting of latitude, longitude pairs. That vector can be approximated well by a relatively small set of complex coefficients. Each coefficient must be multiplied with a corresponding CEOF (a.k.a. principal component, eigenvector, or mode) that is fixed for all time, to produce a set of vectors that when added together reproduce the original Gulf Stream vector. Speaking geometrically, the CEOFs constitute a set of basis vectors that span the space of all known Gulf Stream states (i.e., locations and shapes); an individual Gulf Stream state (location and shape) is produced by linear combinations of the basis set. Speaking figuratively, the CEOFs are the shapes of Gulf Stream patterns and the coefficients are the orientations and sizes of the patterns.

Neural networks have been emerging as a new, viable technology for image analysis and pattern recognition. There are several characteristics of neural networks that make them effective for analyzing large amounts of data rapidly and resistant to noise in the data. Neural networks are composed of many simple computational units (corresponding to biological neurons) that work in unison to process information. There is not programming of the network in the traditional sense; rather the weights that connect the neurons are "learned" by the network through repeated applications of input data for which the desired result is known. Thus, a network can be presented with an infrared image or other input data, and it can process that data based on the information presented during training. The network is tolerant of noise since it has learned the salient features of an image during training, and the noise is in some sense averaged out. A number of neural models for pattern recognition have recently produced promising results and are now being employed on larger applications. Among the more prominent neural paradigms used are the Neocognitron[4] and Back-Propagation model[5].

The Naval Ocean Research and Development Activity (NORDA) Remote Sensing Branch is already performing research into the interpretation of imagery data and has developed an edge-detection algorithm to compute the position of sea surface temperature (SST) gradient fronts in infrared (IR) imagery[6]. The immediate need is to identify the Gulf Stream among the fronts. To say it another way, the Gulf Stream is the pattern to be recognized in a NORDA edge image, and other fronts constitute noise in that edge image.

The opportunity exists, therefore, to explore the capacity of neural networks to recognize the Gulf Stream pattern (represented by CEOF coefficients) within the noise of a NORDA SST edge image.

2.0 TECHNICAL APPROACH

2.1 Objectives

The Phase I work has as its objective to test whether a credible Gulf Stream can be produced by a neural network that has inputs derived from imagery, and has CEOF coefficients as outputs.

2.2 Issues

The basic capability at risk during Phase I is whether a neural network can produce meaningful coefficients for complex empirical orthogonal functions (CEOFs) whose structures were not available to the network. That is, are the patterns represented by coefficients of CEOFs appropriate for neural network technology. This risk resides in several detailed issues that require testing during Phase I. We presume that attributes of neural networks, i.e. capability to recognize patterns in noisy imagery, will be attained in Phase II if we can demonstrate suitability of a CEOF coefficient as a "pattern."

We must determine the neural network connections and weights among nodes that produce meaningful values for CEOF coefficients. These properties of the network are determined by applying one of several candidate learning algorithms operating on an initially randomly connected network and an extensive training set. This leads to several issues.

- What constitutes an appropriate training set for the network?
- What is the criterion for a meaningful CEOF coefficient?
- What, if any, neural network training procedure is capable of producing meaningful coefficients for CEOFs from the chosen training set?
- What is an appropriate configuration of nodes and layers to produce meaningful CEOF coefficients?

- How sensitive to the configuration of hidden layers and nodes is the production of meaningful CEOF coefficients?

CEOFs computed by Molinelli and Flanigan[2] were expressed as vectors with elements every ten nautical miles downstream. Operational use would provide latitude and longitudes of a possible Gulf Stream location derived from SST edge imagery that could not be associated a priori with distance downstream. This leads to the next issue.

- Can input nodes representing positions on a latitude-longitude grid produce meaningful CEOF coefficients?

Once the above issues have been resolved it becomes appropriate to work out details of noise discrimination, conditioning of input data, and increase in resolution and accuracy of the neural network output. But unless these first issues are resolved, the use of neural networks for identification of the Gulf Stream or any acoustically significant front can not be considered feasible.

2.3 Approach

Our approach is to use a series of actual Gulf Streams produced by NORDA between January 1986 and June 1987 to develop a neural network and test its capabilities. These Gulf Streams are part of the Mesoscale Product[7] and are defined between longitudes 50°W and 75°W as shown in Figure 3. They are derived by human analyst using not only IR SST imagery but also GEOSAT altimetric profiles. There are 86 Gulf Streams represented by latitude-longitude pairs at inflection points stored in computer files; the complete set is listed in Table 1. This set of Gulf Streams constitute our first candidate training set.

We use the CEOF software already developed in previous work[2]. New CEOFs were defined for the above data set. To illustrate these modes we plot the ten dominant modes in Figure 4; please recognize that in order to produce a graph that is easily interpreted, we do not plot the modes alone, but instead, plot the modes after multiplication by complex coefficients that span the range of observed coefficients in the set, and, in the case of modes greater than one, add the result to the mean value of mode 1. To demonstrate feasibility we consider it sufficient to define the values of the first three mode

Table 1. List of 86 Gulf Streams Pairs at Inflection Points Stored in Computer Files

FILE NO.	NAME	DATE	FILE NO.	NAME	DATE
1	MESO002.DAT	JAN 10, 1986	44	MESO057.DAT	AUG 29, 1986
2	MESO003.DAT	MAR 10, 1986	45	MESO058.DAT	SEP 3, 1986
3*	MESO004.DAT	FEB 21, 1986	46	MESO059.DAT	SEP 5, 1986
4	MESO005.DAT	FEB 12, 1986	47	MESO060.DAT	SEP 10, 1985
5	MESO006.DAT	FEB 14, 1986	48	MESO061.DAT	SEP 12, 1986
6	MESO007.DAT	FEB 19, 1986	49*	MESO062.DAT	NOV 24, 1986
7	MESO008.DAT	FEB 21, 1986	50	MESO063.DAT	NOV 28, 1986
8	MESO009.DAT	FEB 26, 1986	51	MESO064.DAT	DEC 3, 1986
9	MESO010.DAT	FEB 28, 1986	52*	MESO067.DAT	DEC 12, 1986
10	MESO011.DAT	MAR 5, 1986	53	MESO068.DAT	DEC 17, 1986
11	MESO012.DAT	MAR 7, 1986	54	MESO069.DAT	DEC 19, 1986
12	MESO013.DAT	MAR 12, 1986	55	MESO070.DAT	DEC 23, 1986
13	MESO014.DAT	MAR 14, 1986	56	MESO072.DAT	MAY 30, 1986
14	MESO015.DAT	MAR 19, 1986	57	MESO074.DAT	JAN 9, 1987
15	MESO016.DAT	MAR 21, 1986	58	MESO076.DAT	JAN 16, 1987
16	MESO017.DAT	MAR 26, 1986	59	MESO078.DAT	JAN 30, 1987
17	MESO019.DAT	MAR 28, 1986	60	MESO079.DAT	FEB 6, 1987
18*	MESO020.DAT	APR 2, 1986	61	MESO080.DAT	FEB 11, 1987
19	MESO021.DAT	APR 4, 1986	62	MESO081.DAT	FEB 11, 1987
20	MESO022.DAT	APR 9, 1986	63	MESO082.DAT	FEB 13, 1987
21	MESO024.DAT	APR 16, 1986	64	MESO086.DAT	FEB 27,, 1987
22	MESO025.DAT	APR 18, 1986	65	MESO087.DAT	MAR 4, 1987
23	MESO026.DAT	APR 23, 1986	66	MESO088.DAT	MAR 6, 1987
24	MESO027.DAT	APR 25, 1986	67	MESO089.DAT	MAR 11, 1987
25*	MESO029.DAT	MAY 7, 1986	68	MESO091.DAT	MAR 23, 1987
26	MESO032.DAT	MAY 16, 1986	69	MESO092.DAT	MAR 25, 1987
27	MESO033.DAT	MAY 21, 1986	70	MESO093.DAT	MAR 27, 1987
28*	MESO034.DAT	MAY 23, 1986	71	MESO094.DAT	APR 1, 1987
29	MESO040.DAT	JUN 18, 1986	72*	MESO095.DAT	APR 3, 1986
30	MESO041.DAT	JUN 20, 1986	73	MESO097.DAT	APR 10, 1987
31	MESO042.DAT	JUN 25, 1986	74	MESO098.DAT	APR 14, 1987
32	MESO043.DAT	JUN 27, 1986	75	MESO099.DAT	APR 16, 1987
33	MESO044.DAT	JUL 2, 1986	76	MESO101.DAT	APR 24, 1987
34*	MESO045.DAT	JUL 9, 1986	77	MESO102.DAT	APR 28, 1987
35	MESO046.DAT	JUL 11, 1986	78	MESO103.DAT	MAY 1, 1987
36	MESO047.DAT	JUL 16, 1986	79	MESO106.DAT	MAY 12, 1987
37	MESO049.DAT	JUL 30, 1986	80	MESO107.DAT	MAY 15, 1987
38	MESO050.DAT	AUG 1, 1986	81	MESO108.DAT	MAY 19,.1987
39	MESO051.DAT	AUG 6, 1986	82	MESO109.DAT	MAY 22, 1987
40*	MESO052.DAT	AUG 8, 1986	83	MESO110.DAT	MAY 27, 1987
41	MESO053.DAT	AUG 13, 1986	84	MESO113.DAT	JUN 5, 1987
42	MESO055.DAT	AUG 22, 1986	85	MESO114.DAT	JUN 9, 1987
43	MESO056.DAT	AUG 27, 1986	86	MESO115.DAT	JUN 12, 1987

*WITHELD FROM TRAINING SET FOR TESTING

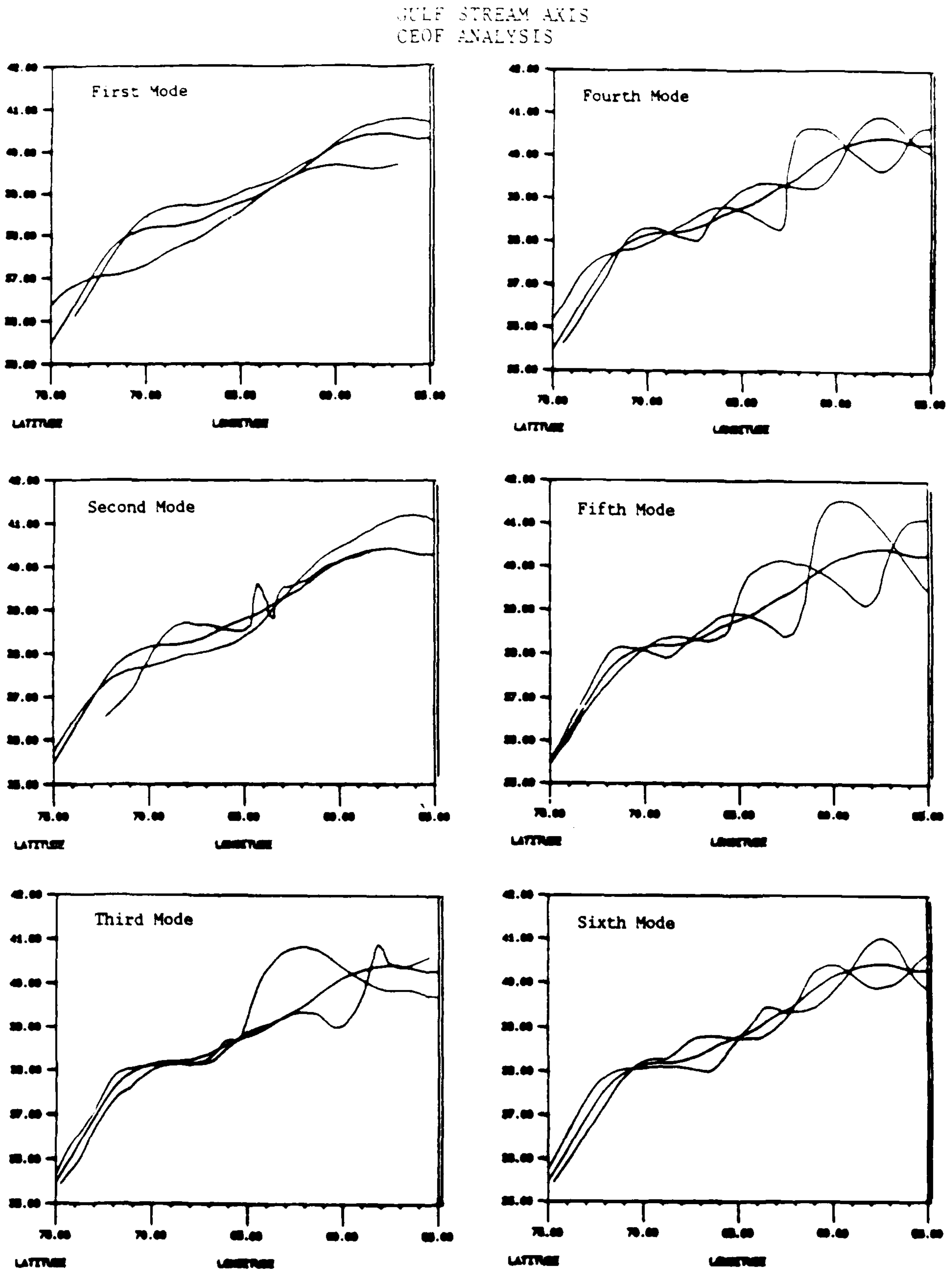


Figure 4. Illustration of the ten dominant CEOF modes. Each mode is shown after multiplying on one mean and two extreme complex coefficients. For modes 2 through 10 this result is then added to the mean of mode 1.

GULF STREAM AXIS

CEOF ANALYSIS

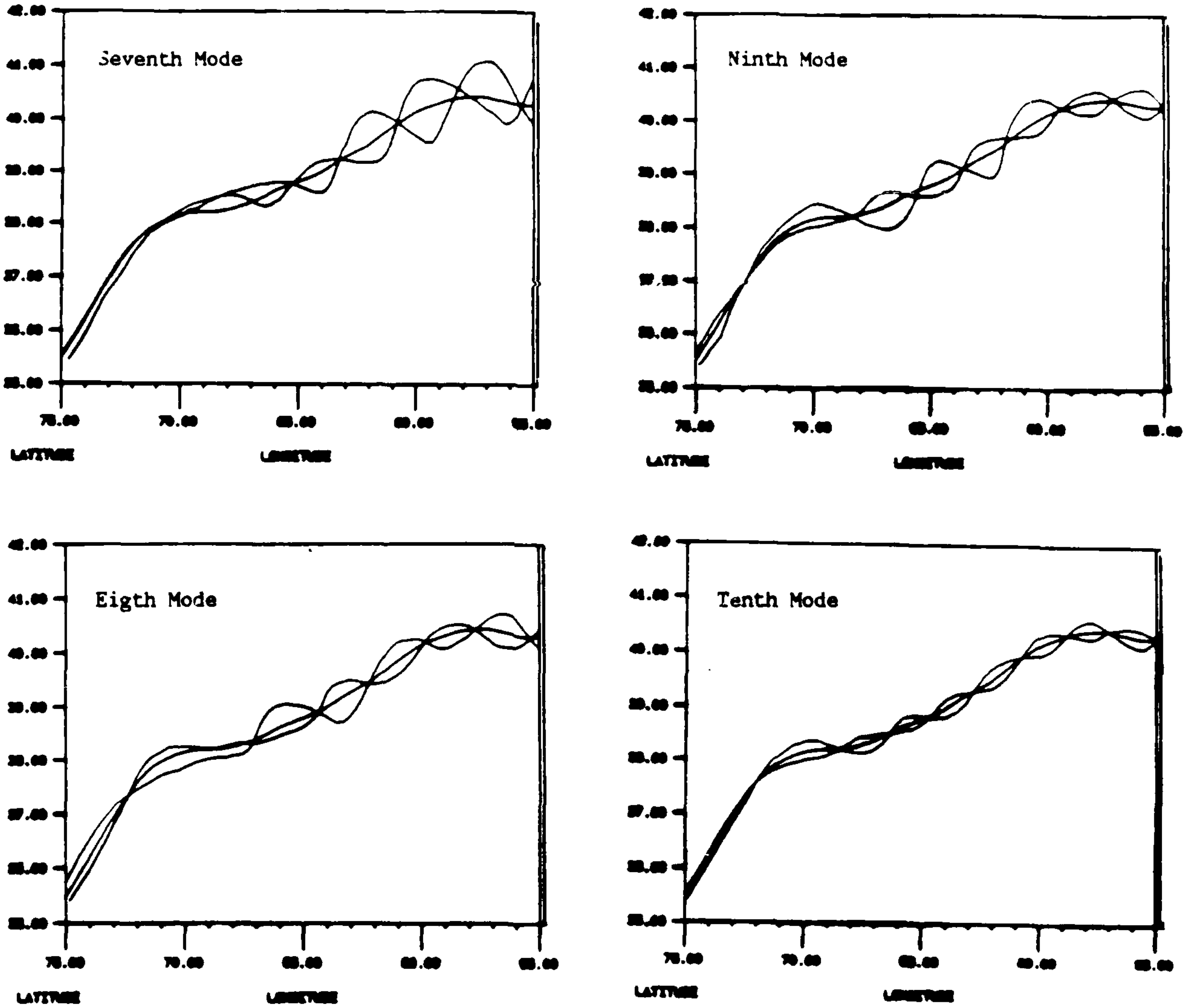


Figure 4. (continued)

coefficients. Together these three modes account for more than 97% of the displacements of the Gulf Stream. Higher accuracy could be attempted in Phase II by using more modes.

As a second candidate for the training set, we obtained NORDA edge images such as shown in Figure 2. However, there are only a few dozen views of the sea surface clear enough to span the domain during our 18 months of Mesoscale Product Gulf Streams. Our previous experience with neural network training led us to conclude that a substantially larger set of images would be required for training to converge in the presence of the noise (other SST fronts) in these images. Nevertheless, we did obtain from NORDA six warmest-pixel composite SST images and the resulting edge images, as well as the nine individual SST images that contributed to the composites, and their edge images. These are listed in Table 2. In all cases the edges were computed using the 16x16 pixel option of the edge detection software developed at NORDA by Holyer and Peckinpaugh[6] because the other options produced perceptibly more fine grained noise. Even though the edge images could not be used as a training set, we did intend to use these images as test cases for the performance of the network.

Table 2. Images for which Edges are Available

Dates of Edges	Dates of Edges
April 14-17, 1986	May 24, 1986
May 13-16, 1986	May 31, 1986
May 16, 1986	May 31-June 3, 1986
May 17, 1986	June 3, 1986
May 15-18, 1986	June 5, 1986
May 21, 1986	June 3-6, 1986
May 23, 1986	June 10, 1986
May 21-24, 1986	

We agreed that a measure of how meaningful a set of CEOF coefficients generated by a neural network is should be the correlation between the coefficients produced by the neural network and the actual values produced by the CEOF software from the appropriate Mesoscale Product. We would take the coefficients in a test case to be meaningful if they are correlated with the actual values with a correlation coefficient of 0.8 or better. For cases in which there are too few pairs to compute correlation, then agreement of mode coefficients within 20% would be considered meaningful.

We use the commercially available software package, Neuralworks, to establish which training procedure generates a network whose output best converges to the actual coefficients of the training set. Best, in this context, means fewest number of training steps and the smallest discrepancies between the network output and the training set coefficients. Our input in this case is just the 132 latitude-longitude pairs available in each computer file for one Gulf Stream, i.e., 264 nodes. Our output is a set of six nodes--real and complex parts of three CEOF coefficients. We also use the commercial software to vary the number of hidden layers and the number of their nodes. Parameters of the learning algorithm, number of nodes, and scaling of input and output values are all modified empirically at this stage in order to achieve convergence.

This commercial software accesses only limited memory and can not handle the vast input arrays inherent in satellite imagery. Thus our next step is to implement the best training algorithm in a high level programming language (C) under a virtual memory operating system (UNIX) so that two dimensional grid values analogous to pixel values can be used as input. The increase in the number of input nodes requires an increase in the number of hidden nodes. We emulate pixel type input with a 50x50 point grid, giving 2500 input nodes -- an increase by a factor of 10 over the previous case.

At this point we must train this new grid-input network, rewrite our Gulf Stream profiles into this grid type format, and test the grid-input network for convergence. As before, parameters of the learning algorithm number of nodes, and scaling of input and output values are all modified empirically at this stage in order to achieve convergence. We train this network finally with only 77 of the available 86 Gulf Streams, leaving a randomly selected 9 as a test set.

When convergence is achieved, it is appropriate to run the fully trained network on any of the 9 test Gulf Streams. The coefficients produced by the network are then compared to the actual coefficients to determine whether they are well correlated.

We then planned to test the performance of the network with an IR edge image projected onto the input grid. If the performance of the network is degraded, we would then have to define a new training set made up of simulated noisy edges. Such a set could be constructed from Mesoscale Products with random sections of random length missing and with random segments of noise added. The statistics of this random noise may have to be matched carefully to the statistics of SST front noise observed in the six composite images.

Finally, we expected to quantify the performance of the network with statistical measures such as mean and root mean difference between network and Mesoscale Product Gulf Streams, and significance level for the differences.

2.4 Apparatus

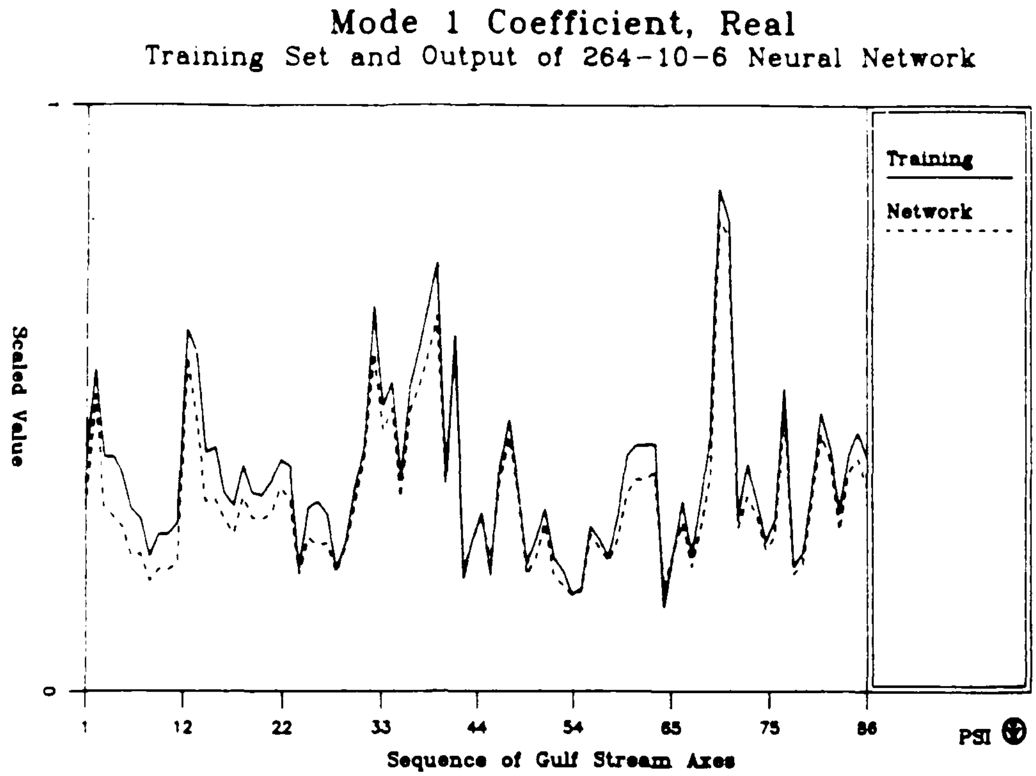
Neuralworks software for which we serve as a beta test site and several INTEL 80386 based microcomputers (386 PC) were used. Neuralworks operates under DOS but is limited in memory, so the 50x50 latitude longitude grid had to be implemented in the virtual memory environment of UNIX on the 386 machines. Imagery is displayed on EGA graphic monitors and hardcopies made on a Laserwriter for which PostScript code had to be written.

3.0 RESULTS ACHIEVED

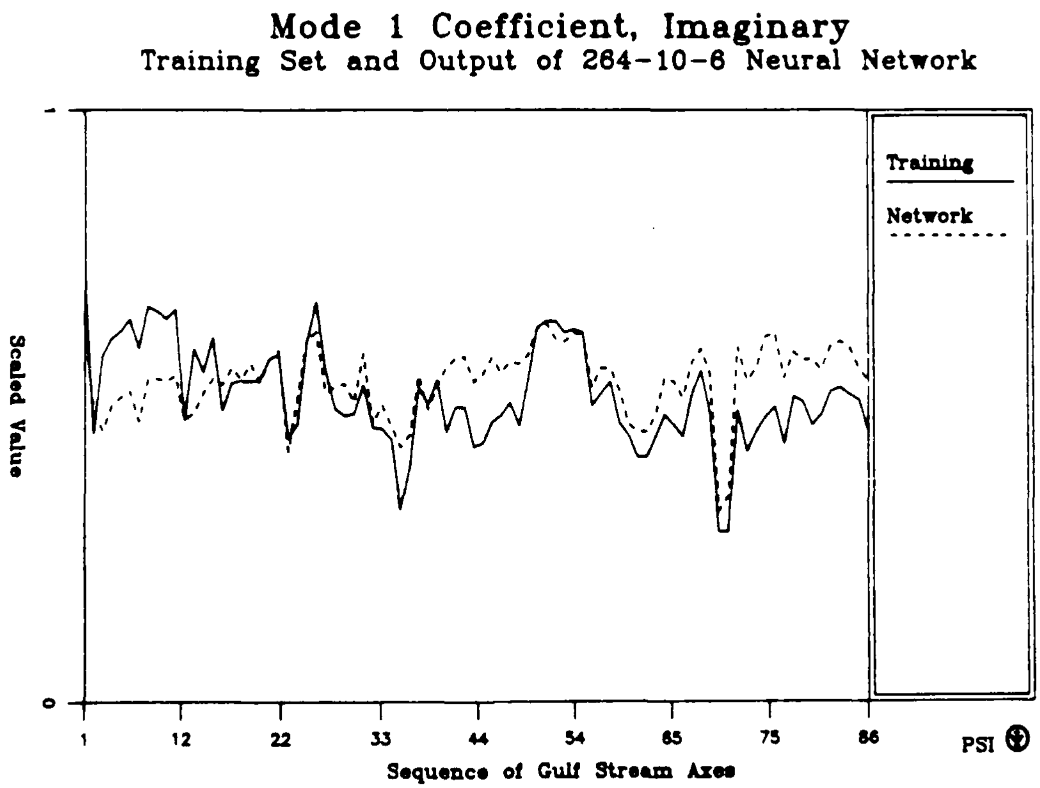
The coefficients we can generate with the Neuralworks network are in excellent agreement with the actual coefficients in the training set. Figure 5 shows how the actual values of the real and imaginary parts of the first three CEOF modes vary over the 86 Gulf Streams used as the training set. Also plotted in Figure 5 are the values produced by the trained network (which is called the 264-10-6 network for reasons soon to be evident) as each Gulf Stream is input to it. The close agreement between the two curves for each coefficient indicates that the network has converged. A neural network can produce meaningful coefficients for CEOF modes. A neural network can generate a continuous Gulf Stream.

We can quantify this agreement by computing for each coefficient a mean and a variance over the ensemble of 86 Gulf Streams; these are listed in Table 3. Table 3 shows that the means of the Neuralworks network typically agree with the actual mean within 3.6%. But what is more important, the 264-10-6 network also mimics the variance in Gulf Stream coefficients -- typically hitting the variance within 11.8% also. The correlation coefficient for the six sets of CEOF mode coefficients is typically better than 0.98.

Figure 5. Excellent agreement between neural network produced and actual mode coefficients for the training set. Here the network is the 264-40-6 network implemented in Neuralworks software. The real and complex parts of the first three modes (plots a through f) are scaled according to Table 4 to fall between 0 and 1 and are plotted against the sequence of Gulf Stream axes from NORDA's Mesoscale Products between January 1986 and June 1987.

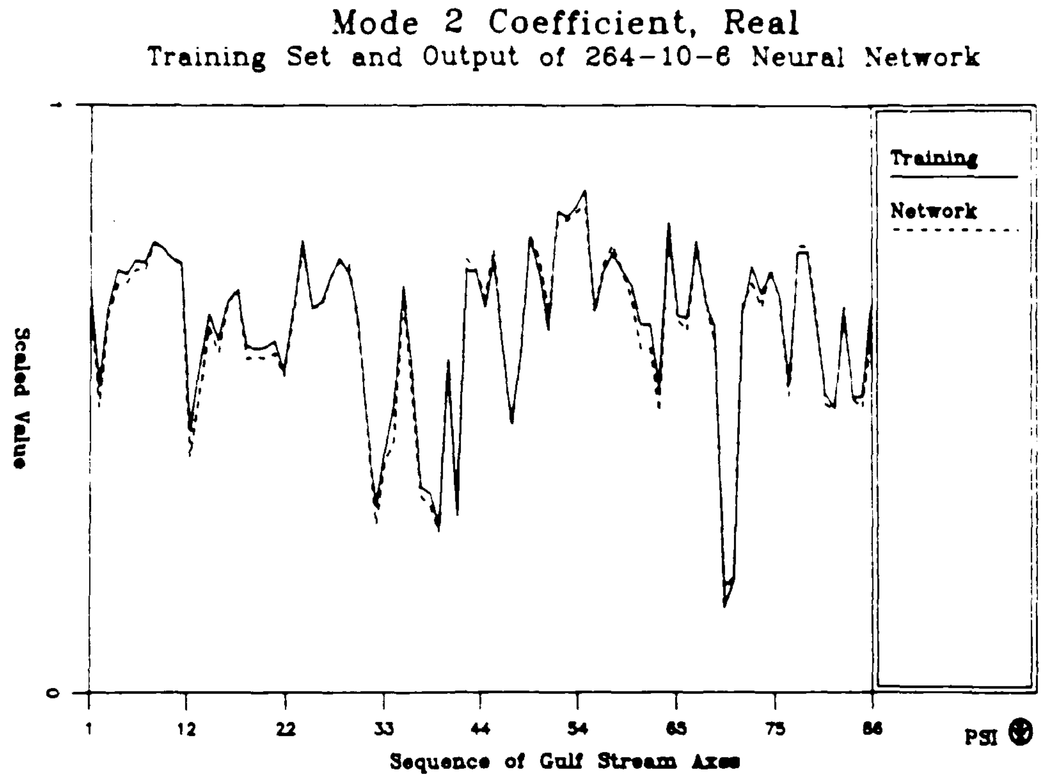


(a)

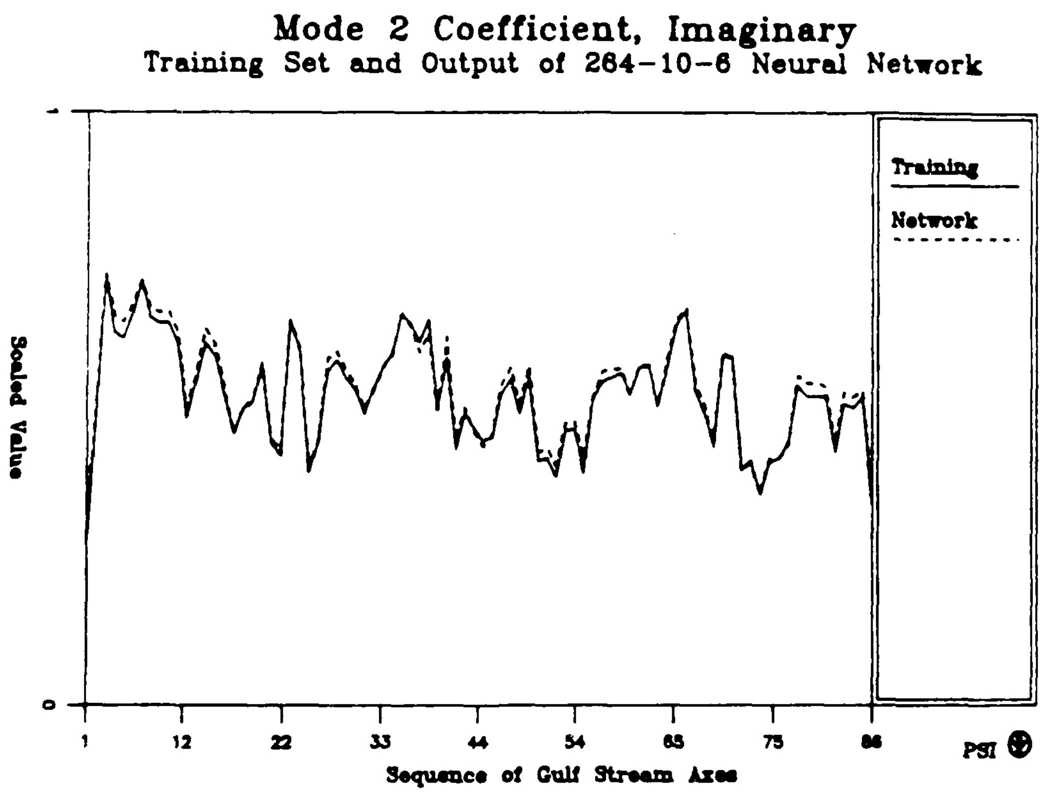


(b)

Figure 5. (a) & (b)



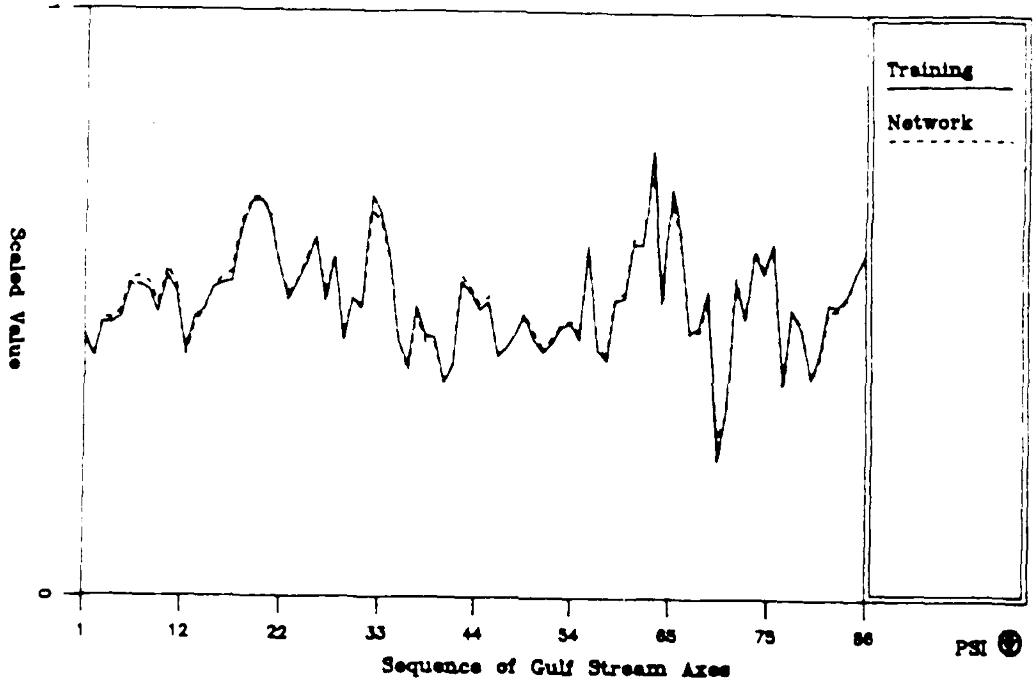
(c)



(d)

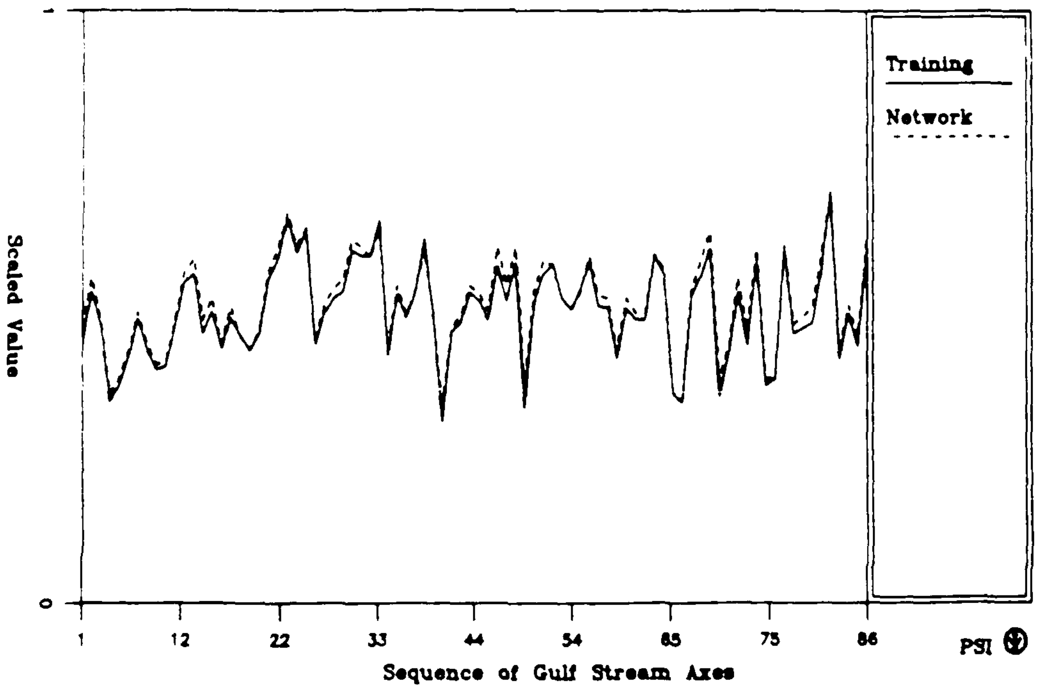
Figure 5. (continued) (c) & (d)

Mode 3 Coefficient, Real
Training Set and Output of 264-10-6 Neural Network



(e)

Mode 3 Coefficient, Imaginary
Training Set and Output of 264-10-6 Neural Network



(f)

Figure 5. (continued) (e) & (f)

Table 3. Mean 8 Variance of 86 Streams for 1st 3 Modes

Mode Coeff.	Actual Mean	Actual Variance	264-10-6 Mean	264-10-6 Variance	Root Mean Square Difference between Network & Actual
1, real	.36686	.01994	.32810	.01669	.00236
1, imag.	.51797	.00703	.543[illegible]	.00362	.00526
2, real	.62294	.02015	.61439	.02122	.00041
2, imag.	.52452	.00795	.53376	.00809	.00019
3, real	.50531	.00785	.50749	.00761	.00009
3, imag.	.49391	.00653	.50644	.00650	.00025

This good agreement is obtained with the following network parameters selected through experiment. The learning algorithm is back propagation[5]; convergence is achieved with 100,000 iterations through the training set with the learning coefficient set to 0.9 and the momentum coefficient set to 0.6. The number of hidden layers is 1; the number of nodes on that layer is 10 (hence the network consists of 264-10-6 input-hiddden-output nodes, respectively). The coefficients placed or retrieved at the six output nodes must be separately scaled to range between the values of 0.2 and 0.8 in order for the higher mode coefficients to converge closely. The scaling is presented in Table 4.

Table 4. Scaling Factors to Convert Values at Output Nodes of the Network into CEOF Coefficients

Network Output Node	Multiply Node Value by	Add Node Value to
1	70.161	670.447
2	34.832	509,545
3	69.680	-42.504
4	35.872	-18.819
5	42.544	-21.590
6	32.653	-16.079

We successfully implemented a new network in the C programming language that would operate on input nodes arranged as a 50x50 grid. The Mercator Projection region between 34°N and 45° N latitude and 75° W and 50°W longitude is mapped into this 50x50 grid. The nominal resolution of the grid is 50 km. The 86 Mesoscale Gulf Streams are mapped onto this grid (Figure 6 shows a sample Gulf Stream on the grid) and used as input to the new neural network. We call the new network the grid-input network, or the 2500-40-6 network, to distinguish it from the earlier network. This network contains 40 nodes in one hidden layer, learns using back propagation, and uses the same scaling for the conversion between output nodes and CEOF coefficients as Table 4. These selections were made a priori based on the experience with the earlier network; no experiments were performed to determine whether performance would improve or degrade with different selections. This network is trained with 77 of the 86 Gulf Streams; 9 Gulf Streams selected at random were held back for testing (as denoted in Table 1). It converged on its final form after 150,000 passes through the training set. This convergence took about 7 days of run time on our 20 megahertz (MHz) machine programmed in C under the UNIX operating system.

Figure 7 shows the variation of coefficients over the training set and the good agreement with coefficients produced by the grid-input network. Table 5 shows that the means of the grid-input network typically agree with the actual mean within 0.7% for the training set. Again, what is more important, the 2500-40-6 network also matches the variance in Gulf Stream coefficients -- typically hitting the variance within 13.0% also. The correlation coefficient for the six sets of CEOF mode coefficients is better than 0.87. This is extremely encouraging because these good measures are achieved without optimizing the parameters of the network. Of further importance is that the processing by the network is extremely fast; it takes less than 1 second to produce three complex mode coefficients from 50x50 gridded input.

The grid-input network does less well with data in the test set (Figure 8 and Table 6), but still achieves agreement within 6.0% for the means, though only within 68% of the variances. The performance in matching the variance is skewed by poor performance on just two axes because the test set is so small. Figure 8 shows good qualitative agreement between axis and image. Table 7 lists the correlations for all preceding cases.

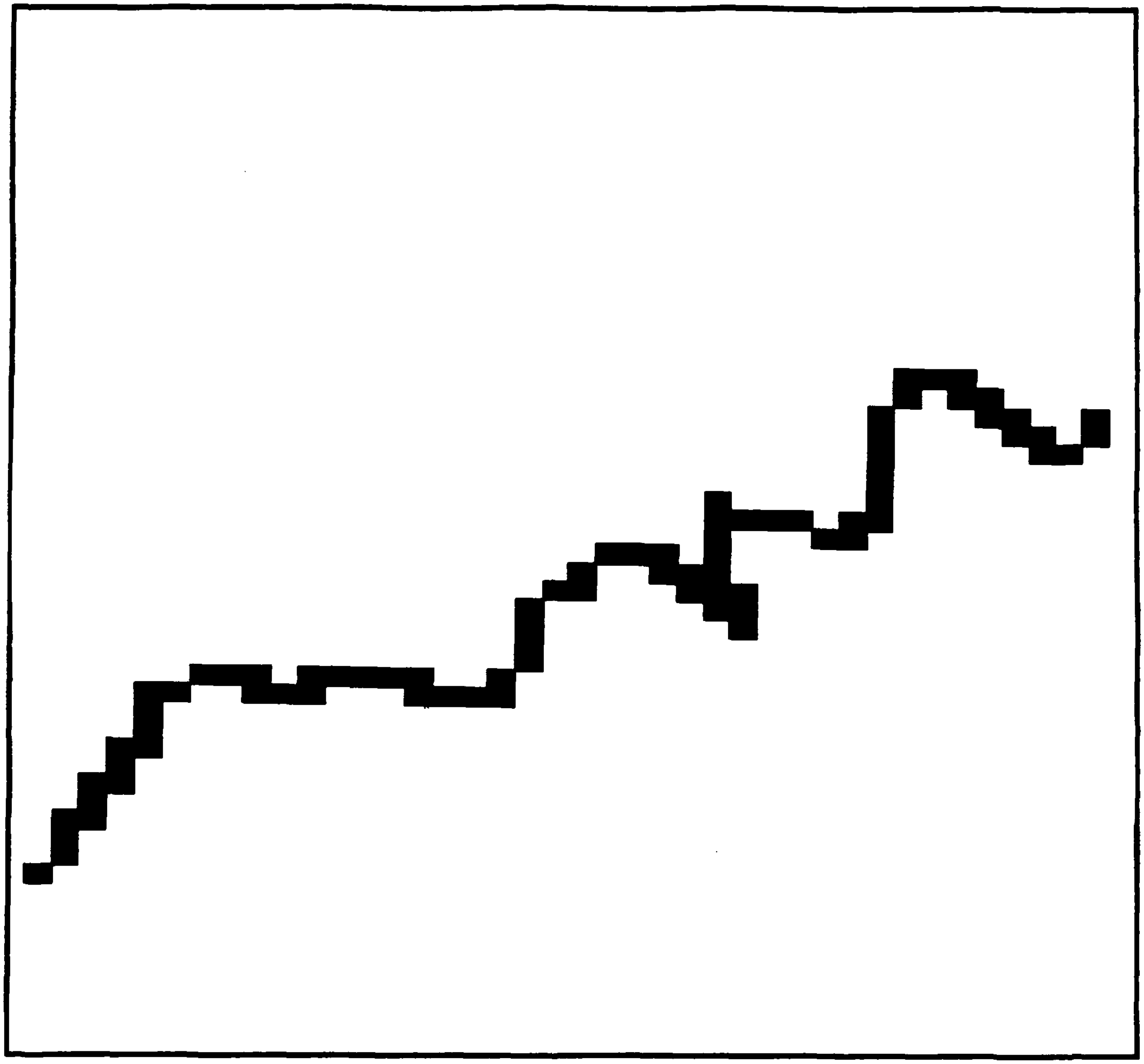
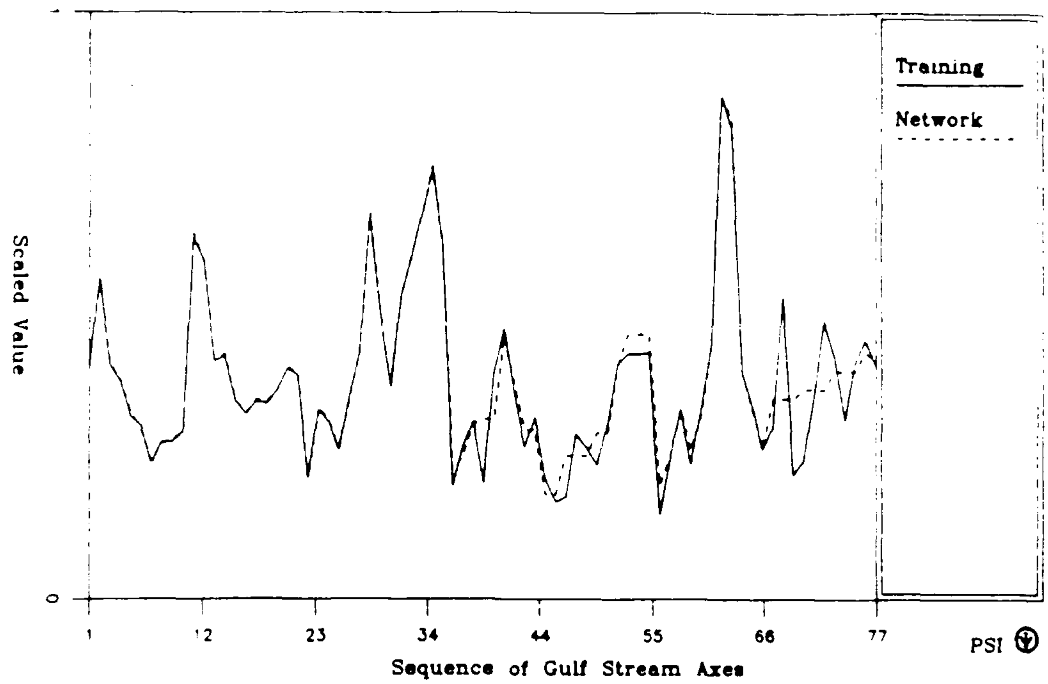


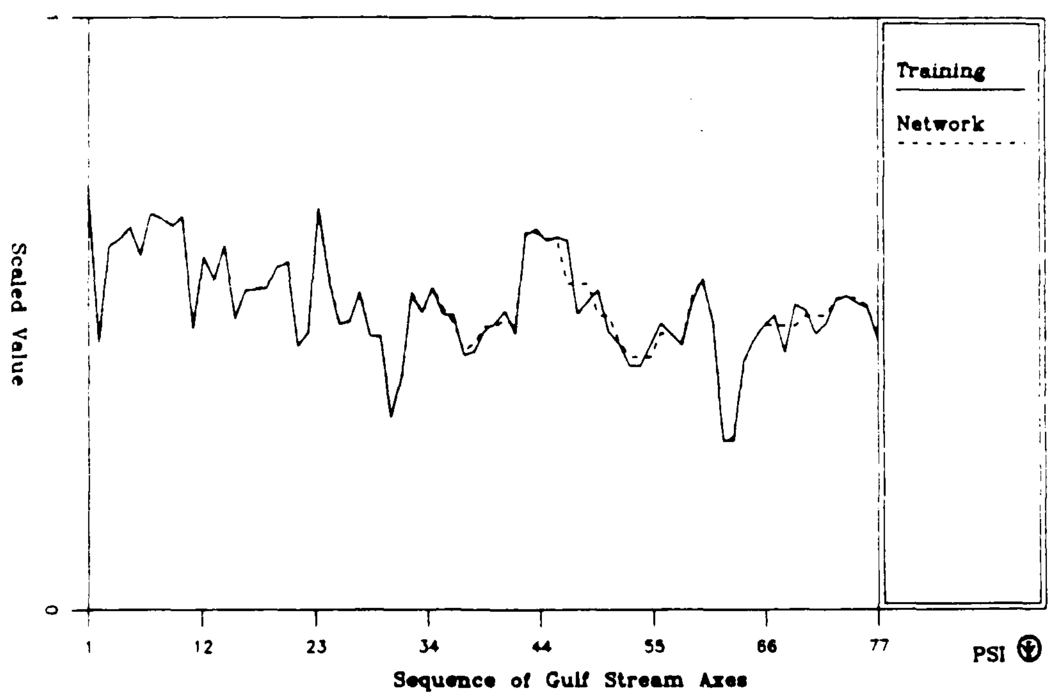
Figure 6. Mesoscale Product Gulf Stream mapped to the 50x50 input grid.

Mode 1 Coefficient, Real
Training Set and Output of 2500-40-6 Neural Network



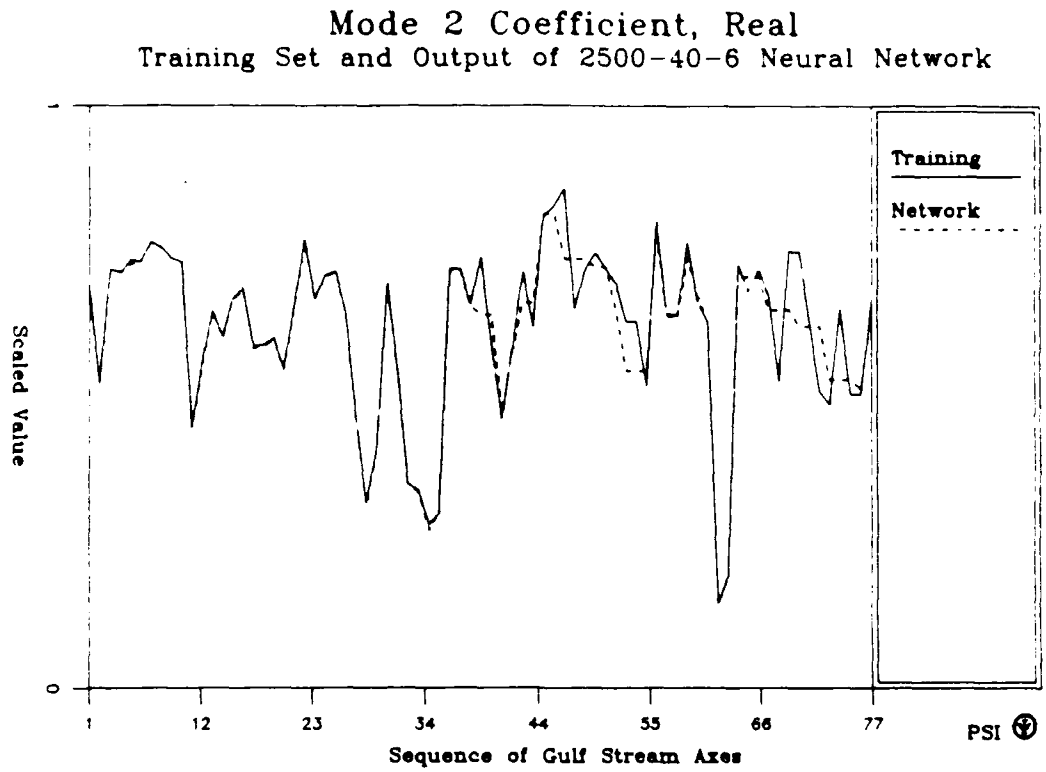
(a)

Mode 1 Coefficient, Imaginary
Training Set and Output of 2500-40-6 Neural Network

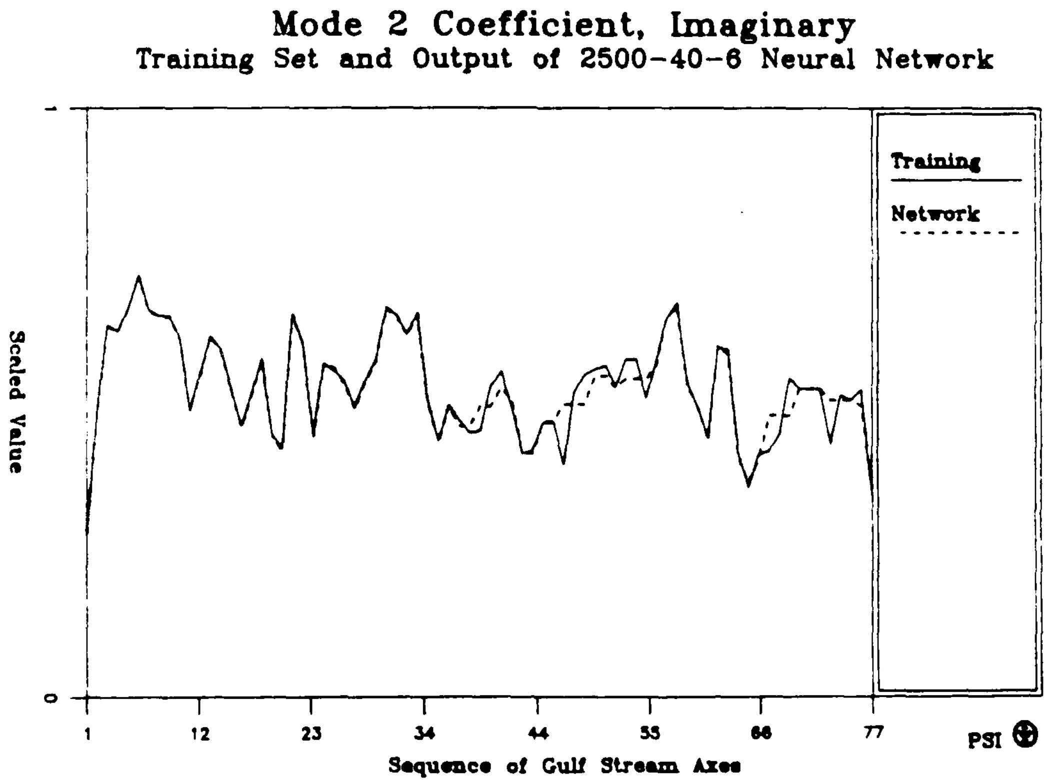


(b)

Figure 7. Same as Figure 5 (plots a through f) but for 2500-40-6 network implemented in our own C language software operating on the training set. Again, excellent agreement between network and actual coefficients.



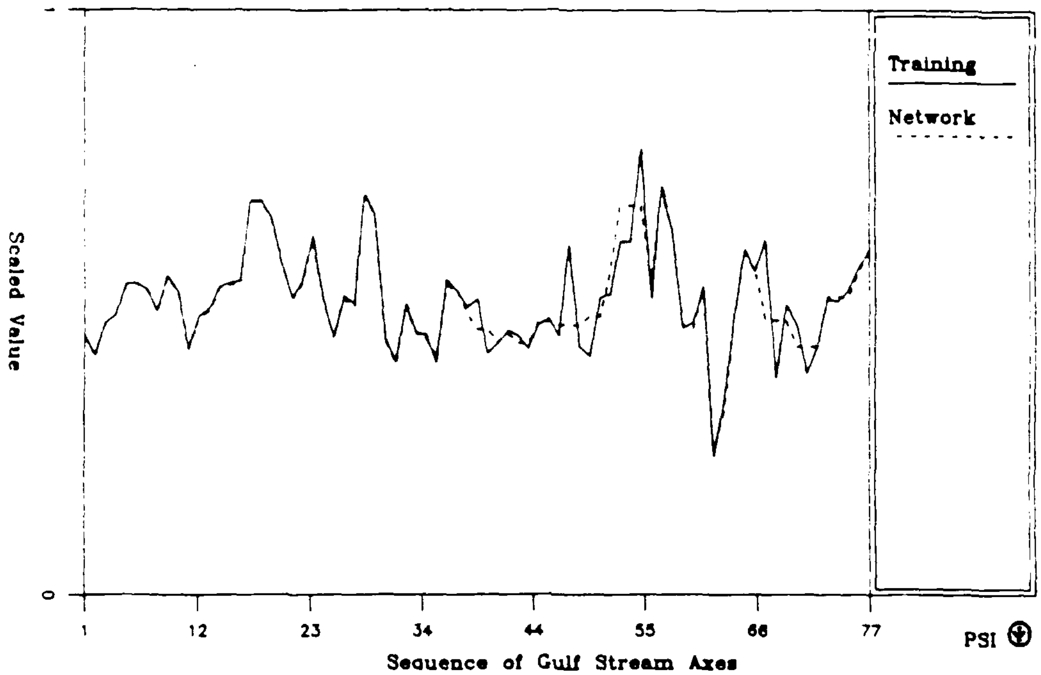
(c)



(d)

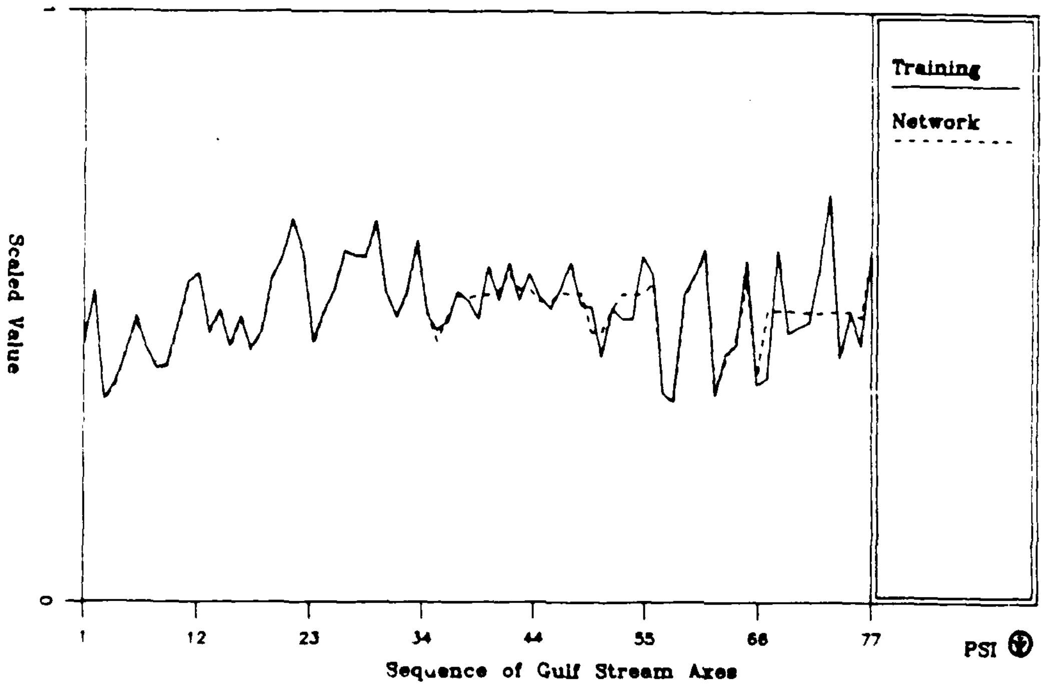
Figure 7. (continued)

Mode 3 Coefficient, Real
Training Set and Output of 2500-40-6 Neural Network



(e)

Mode 3 Coefficient, Imaginary
Training Set and Output of 2500-40-6 Neural Network



(f)

Figure 7. (continued)

Table 5. Mean & Variance of 77 Streams in 2500-40-6

	Actual Mean	Actual Variance	2500-40-6 Mean	2500-40-6 Variance	RMS Error
Coef. 1 Real	.37633	.01889	.37181	.02065	.00165
Imag	.51734	.00696	.51604	.00724	.00024
Coef. 2 Real	.61178	.01922	.61864	.02091	.00175
Imag	.52384	.00671	.52465	.00741	.00048
Coef. 3 Real	.50207	.00707	.50414	.00791	.00113
Imag	.49444	.00445	.49694	.00596	.00136

Table 6. Mean & Variance of 9 Test Streams

	Actual Mean	Actual Variance	2500-40-6 Mean	2500-40-6 Variance	RMS Error
Coeff 1 Real	.32451	.01083	.37834	.02275	.02468
Imag	.53443	.00471	.52649	.00726	.00328
Coeff 2 Real	.65976	.01118	.62632	.02066	.01529
Imag	.52343	.01317	.50572	.00451	.00813
Coeff 3 Real	.51534	.00712	.48515	.00488	.00378
Imag	.46795	.01119	.48532	.00370	.01652

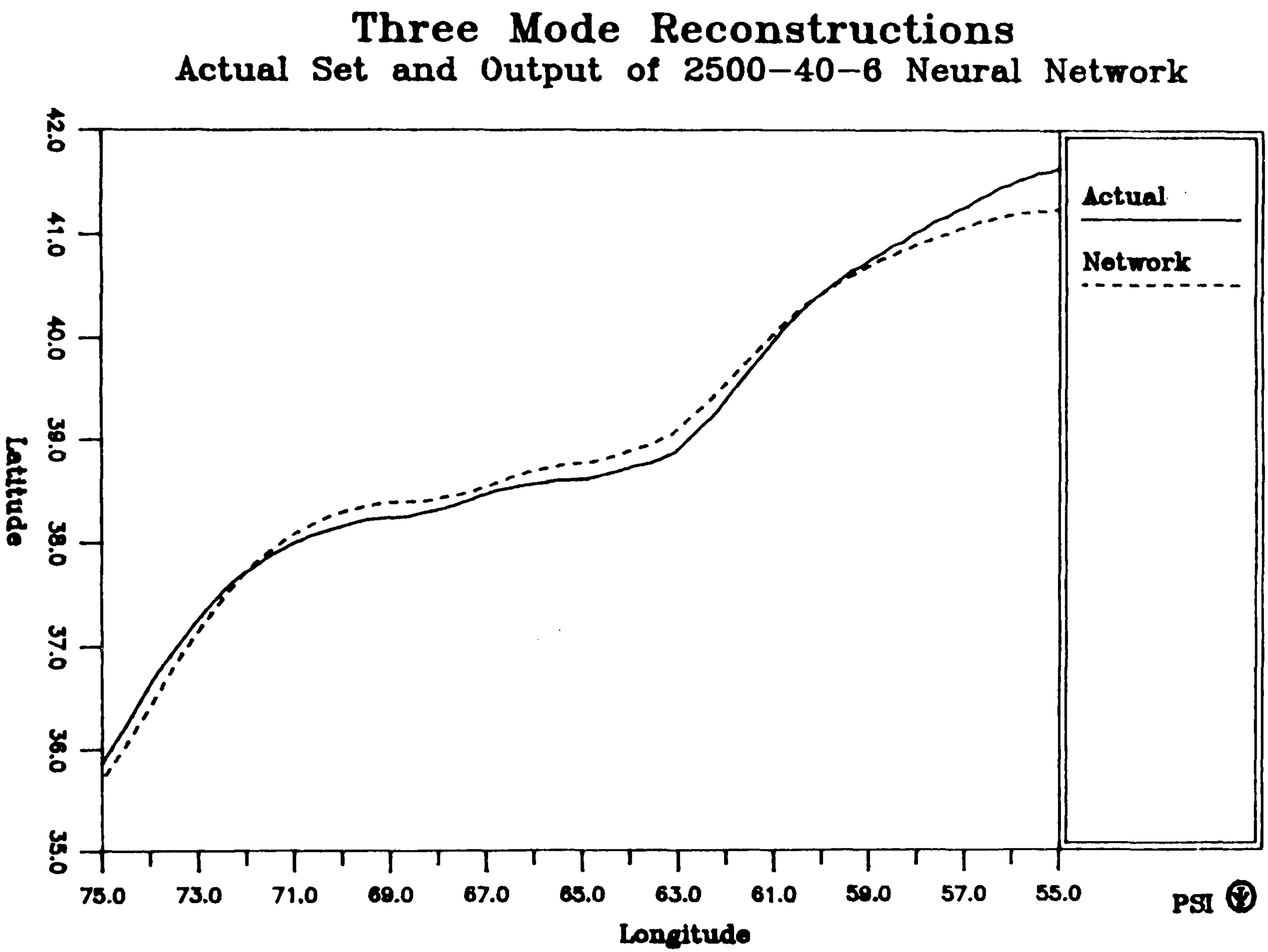


Figure 8. Proximity of 3 modes from grid-input neural network (dashed) to the actual 3 modes for a test Stream.

Table 7. Correlation Coefficients

	Training 264-10-6	Training 2500-40-6	Test 2500-40-6
Coeff 1 Real	.981010	.959822	.387440
Imag	.597494	.983241	.749872
Coeff 2 Real	.992103	.958424	.586563
Imag	.993256	.967478	.643265
Coeff. 3 Real	.994733	.926524	.782846
Imag	.992514	.878790	-.100011

The trained 2500-40-6 network performs moderately well on noisy edge imagery also. The edge image of Figure 2 is transformed to the much coarser 50x50 grid to provide the noisy input shown in Figure 9. In spite of looking nothing like the training set of Gulf Streams, the input does not cause the network to diverge; in fact, the network generates quite reasonable coefficients. A graphical comparison of the resulting 3-mode Gulf Stream is shown in Figure 10 with the actual 3-mode Stream and the edge imagery. The network Gulf Stream is within 60 nm of the actual for most of its length and properly identifies Gulf Stream SST edges by crossing over them. This result is encouraging; however, there are insufficient resources in this Phase I effort to compute the statistical performance of the network under a range of coarse grid noisy edge images.

Figure 10 also demonstrates that the neural network output is connected to the CEOF software so as to produce a neural network derived Gulf Stream; therefore, this result satisfies the final objective of the Phase I research.

The modest successes achieved for a network not optimized for gridded input and not trained for noisy edges indicate that this neural network is robust, i.e., not unstable over a range of parameters. We expect the network to achieve better performance with further experimentation. The fast processing (less than 1 second) of a 50x50 edge image by a previously trained network is a great strength of the method.

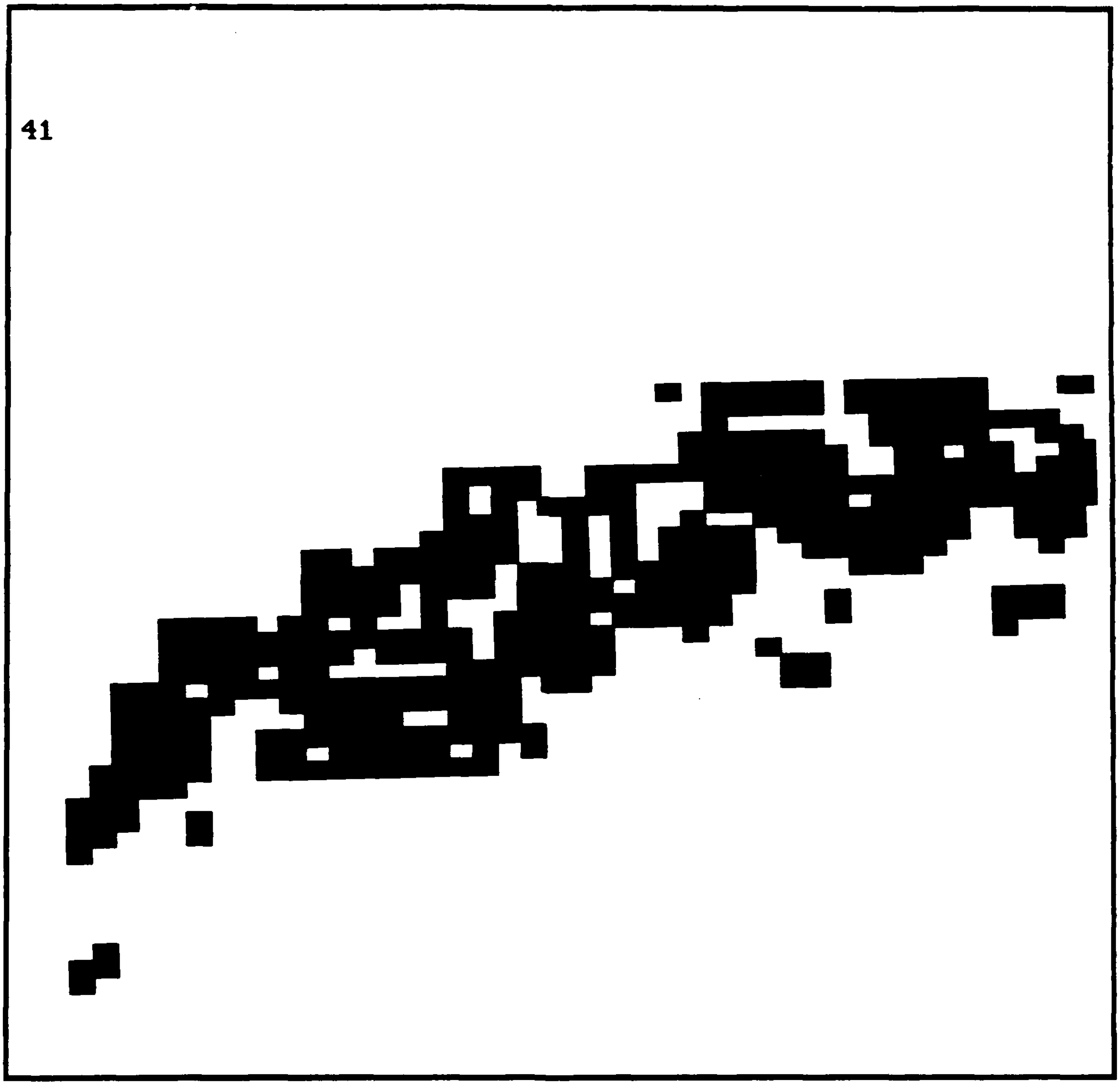


Figure 9. Edge image mapped to the 50x50 input grid.

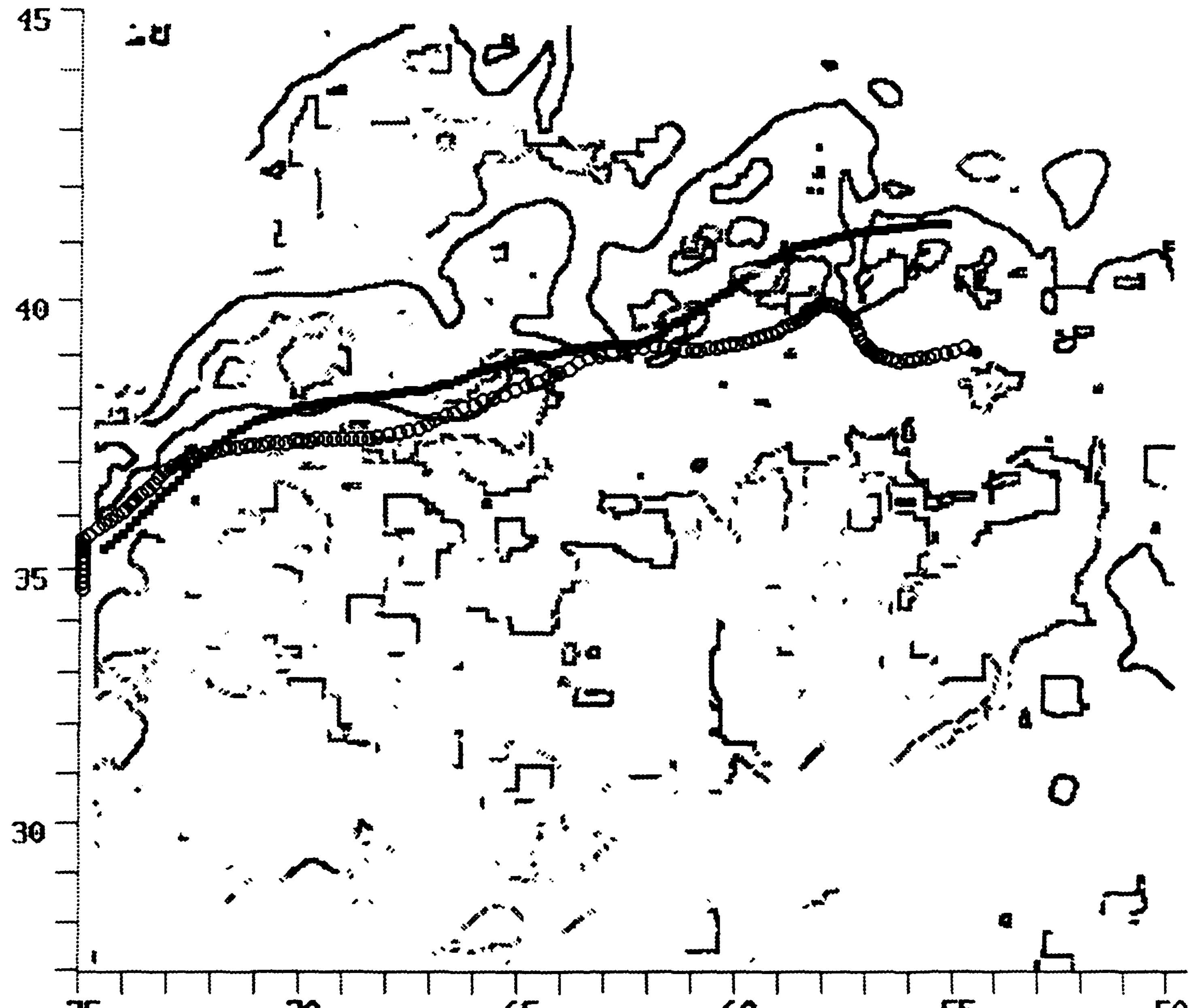


Figure 10. Proximity of 3 modes from grid-input neural networks (open circles) to the 3 modes of the actual Gulf Stream.

4.0 CONCLUSIONS AND RECOMMENDATIONS

PSI achieved all of our Phase I objectives except the statistical analysis of the network's performance. In spite of this, the correlations obtained and qualitative association between a 3-mode reconstructed Gulf Stream and the original IR image does demonstrate the feasibility of the approach. We conclude that neural networks are a viable approach for rapidly recognizing the *acoustically significant Gulf Stream in edge imagery.* We recommend that a full fledged neural network be generated that is optimized for performing on noisy, gridded, higher resolution edge imagery and with enough complex mode coefficients as output so that sufficient accuracy can be attained. The goal of this work should be identification of SST edges associated with the Gulf Stream so that Gulf Stream reconstructions under SST gradients could be accurate within 10 km and elsewhere within 50 km. The interfaces should also be designed for connection to an imagery source (such as TESS) and a decision aid destination (such as NORDA Oceanographic Expert System). Also a methodology should be designed to transport the neural network/CEOF approach to other Fleet Operational Areas with acoustically significant fronts observable with satellite imagery.

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